Detection Probability Using Relative Clutter in Infrared Images

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***Abstract* - Clutter plays a very important role in the area of machine and human-in-the-loop target acquisition. A great deal of interest has recently been shown in assessing several different definitions of clutter. In spite of so many definitions available, no single clutter definition has been agreed on by the target acquisition modeling community as being the best. In this paper, we develop a new clutter metric, called relative clutter, based on factor analysis which is extensively used for statistical analysis. This relative clutter combines many definitions of clutter. Different methods for calculating the relative clutter based on the magnitude of the eigenvalues obtained from the correlation matrix are suggested in this paper. The relative clutter of many images is analyzed. The relative clutter is used to calculate probability of detection on Night Vision Lab (NVL) Terrain Board Infrared (IR) images**

***Index Terms*-clutter, signal-to noise-ratio, image processing, human perception, computer vision, automatic target recognition (ATR).**

I. Introduction

There are many definitions of clutter currently used in the literature of image processing and target acquisition modeling.[1,2,3,4,5,6] Some of these metrics are listed below;

mean radiance or ΔT metric
statistical variance metric
probability of edge metric
complexity metrics

There is no definition which is clearly the best in all cases for the ATR community. The object of this paper is to give a unified definition of clutter which takes into account the different definitions available in the literature. The present study is meant serve as a proof of principle study. The images used for this study were obtained from the Army's NVL Terrain board simulator. The clutter metrics combined in this study to form a relative clutter metric are the following

Der metric
POE metric
Scheider-Weathersby metric
Mean radiance
Standard deviation of background

a)Der Clutter Metric

Originally the Der metric was devised as a method that could be used to predict the false alarm rate of a given algorithm. The approach was the following: a double window was convolved one pixel at a time over the image. The size of the inner window was the maximum size of the largest target we were using at the time. These two features, minimum and maximum, were chosen arbitrarily. At each pixel location the algorithm decides whether the new pixel is in the same intensity space as the one previously examined and then also whether it fits into the inner window. When an intense region of the image of approximate target size is found, that region is catalogued. The principle behind the Der method is to then multiply the distribution of the target -like areas by the probability of detection distribution. The result should then give the predicted false alarm rate for an algorithm with a given probability of detection distribution. Now if one simply counts the number of Der objects in the image, that number should indicate the number of target-like objects in the scene, hence, a measure of clutter.

b)POE Metric

The Probability of Edge metric is meant to determine the relationship between the human visual detection system and the statistics of the color or black and white images. First, the image under consideration is processed with a difference of Gaussian (DOOG) filters and is thresholded. This procedure is intended to emulate the early vision part of the human.[5] Then the number of edge points are counted and are used as the raw metric. The procedure for calculation proceeds as follows: first the image is divided into blocks twice the apparent size of the target in each dimension. Then a DOOG filter as described in [11] is applied to each block to emulate one of the channels in preattentive vision with the net effect being to enhance the edges. As discussed in [5] the histogram of the of the processed image is normalized and then a threshold, T, is chosen based on the histogram. The number of points that exceed the threshold in the i'th block are computed as $POE_{i,T}$.

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The POE metric is then computed in a manner similar to the statistical variance technique,

$$POE = \frac{1}{N}\sum_{i=1}^{N} POE_{i,T}^{2} \ . \qquad (1)$$

As the authors in [5] point out, it is known by the work of Marr [12] and other vision researchers that preattentive vision is highly sensitive to edges.

c) Schmieder and Weathersby metric

Schmieder and Weathersby [1] have proposed the concept of a RMS clutter metric of the spatial-intensity properties of the background. To date it is the most commonly used clutter measure. The Schmieder and Weathersby clutter metric is computed by averaging the variance of contiguous square cells over the whole scene:

$$clutter = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \sigma_i^2} \qquad (2)$$

where σ_i^2 is the variance of pixels within the ith cell, and N is the number of cells or blocks the picture has been divided into. Typically N is defined to be twice the length of the largest target dimension. The signal-to-clutter ratio (SCR) of the image is then given by the average contrast of the target divided by the clutter in (2).

The variance in (2) has been shown in [2] to be equivalent to,

$$\sigma_i^2 = \frac{1}{K}\sum \left(X_{ij} - U_i\right)^2 \qquad (3)$$

where K is the number of pixels per cell, X_{ij} is the radiance of the j'th pixel in the i'th cell,
and U_i is the i'th cell mean radiance.

It has been noticed [13] that equation (2) was compared by Schmieder and Weathersby with experimental detection times for observers looking at computer generated images of rural scenes with embedded targets. A good correlation between the average detection time and SCR value was found.

By way of comparison, the mean and standard deviation of the background were also taken as clutter measures.:

c) mean of background

d) standard deviation of background

The original data is shown in Tables I. There were 24 images in total. The images were taken using the terrain board simulator of the US Army NVL in Ft. Belvoir, VA. The image set had three types of clutter and each image had Army vehicles in it of different sizes. The total image size is 512x512 pixels. We used factor analysis to obtain a relative clutter based on the aforementioned 4 definitions (a-d) of clutter. This new definition of clutter, we hope, can be expanded to encompass all the current existing definitions and act as a common denominator for them.

II. Method

For convenience the algorithm for relative clutter is summarized as follows;

- Read the input matrix, M
- Find the correlation matrix, R
- Calculate the Eigenvectors and Eigenvalues,
- Loading = sqrt(eigenvalues)*eigenvectors,
- Perform a Varimax rotation to get the rotated factor loading matrix,
- Define an L matrix to be the variance of the rotated factor loading matrix,
- Compute the inverse correlation matrix, R^{-1}
- Compute T = (R^{-1})* F_r
- Determine normalized Matrix and name it as Z,
- Compute Z*T,
- The relative complexity values $C_{rel} = Z*T*L^T$.

By way of example of the flow of the algorithm for he computation of relative clutter, Table II shows the correlation matrix of the high noise case. Table III shows the corresponding eigenvector matrix and Table IV shows the loading factors before and after Varimax rotation with 2 loading factors. Table V shows the normalized Varimax adjusted clutter values and Table VI shows the rotated variances which lead to the relative clutter values. Table VII shows the final clutter metrics.

Algorithm: Factor Analysis

Factor analysis is a generic name given to a branch of statistics whose primary purpose is data reduction and summarization. Generally speaking, factor analysis confines itself to the problem of analyzing the interrelationships among a large number of variables(e.g., clutter values, clutter types, and observer responses) and then explaining these variables in terms of their underlying dimensions or factors. Factor analysis is an interdependence technique I which all variables are considered simultaneously. Each of the observed variables, clutter metric in this case, is considered as a dependent variable that is dependent on some more fundamental set of factors. In this paper, the factor analysis is applied to the covariant relationship among different clutter metrics in terms of a few underlying factors. Perception metrics in general, and specifically clutter metrics, can be grouped by their correlation, i.e. all metrics within the particular group are highly correlated among themselves but have relatively small correlation with metrics in a different group. In which case each group of variables represents a single underlying factor, which is responsible for the observed correlation. The factor analytic procedure will be shown to serve as a basis for the development of a relative clutter metric.

Factor analysis is usually concerned with two major problems:

1) Reducing the dimensionality of the original data space, whether by principal components or some other factoring procedure-

2) Rotation of the factor loading solution in the reduced space to some more interpretable
orientation and recomputation of factor scores in the new orientation.

The correlation matrix, which indicates the relationships among the variables, is a fundamental element in factor analysis. Since R is symmetric, all distinct eigenvectors are real and orthogonal, and its singular value decomposition has the form as follows:

$$R = U*D*U^T$$

where U is an orthogonal matrix(UU'=U'U=I), whose columns are the eigenvectors of R, and D is a diagonal matrix whose entries are the eigenvalues of R. Since R is a product moment matrix, all diagonal entries of D are nonnegative.

The whole matrix of factor loadings can be found from the matrix product:

$$F = U*D^{1/2}$$

where it should be noted that the sum of squares of each column of component loadings equals the component's eigenvalue, and the sum of squares of each row of component loadings equals that variable's communality. In the factor analysis in this research, we identified the factor loadings from the data set. Once factors are identified we determine a set of new common factors fr1, fr2, ..., which are linear combinations of the original factors and which are uncorrelated with unit variance. In this way, the new set of factors also satisfy the factor model. The method used for obtaining the new set of factors is called an orthogonal factor rotation, whose objective is to obtain some meaningful factors so that the factor structure is simplified. Several different techniques for orthogonal factor rotation are discussed in a number textbooks[9,10]. In our research, we use the most popular rotation schemes, which is Kaiser's Varimax procedure to get the factor loadings. The Varimax rotation attempts to simplify the columns of a factor matrix. The rotation attempts to have each column consist of either ones or zeros. Only a subset of columns from original factor pattern is selected for rotation. The selection criterion is generally based on the eigenvalues corresponding to columns in our case, we choose the two columns of the original factor loading matrix F with the largest two eigenvalues for rotation purposes, which is denoted as F'. Then we can obtain the transformation matrix from initial loadings to the final loadings:

$$T=R^{-1} * F_r$$

where F_r is the matrix of rotated factor loadings.

For each image, a raw data vector of three or four clutter metrics is input to the factor analysis. This raw data vector is converted to a new standard score vector, Z. Then T is used to map a matrix of standardized clutter metrics, Z, onto the identified orthogonal factor dimensions. Thus the relative clutter, C_r, can be represented as follows:

$$C_r = Z*T*L^T$$

where L is a vector of eigenvalues associated with the specific factor dimensions. As mentioned above each eigenvalue is the sum of squares of each column of component loadings. The i'th entry of C_r represents the relative clutter of the i 'th image in the image set. Following are the tables resulting from such a procedure.

TABLE I
CLUTTER METRIC VALUES FOR THE INFRARED IMAGES

der	poe	schmieder	mean_bkg	std_bkg
188	0.001	19.001	3.797	0.251
174	0.001	19.204	4.353	0.238
166	0.003	22.004	2.921	0.323
163	0.000	15.581	3.620	0.307
159	0.004	19.428	2.955	0.375
278	0.002	15.743	3.450	0.421
288	0.003	17.071	3.456	0.204
322	0.004	15.204	3.462	0.231
334	0.005	15.967	3.707	0.295
334	0.004	15.770	3.584	0.204
333	0.003	15.432	3.388	0.425
338	0.000	15.497	3.558	0.218
333	0.000	16.906	4.146	0.223
481	0.008	19.704	3.724	0.264
489	0.003	17.695	3.877	0.287
568	0.005	17.984	3.630	0.553
337	0.001	21.859	3.155	0.308
320	0.000	17.502	3.803	0.289
324	0.001	18.200	3.855	0.283
347	0.001	21.139	4.092	0.169
283	0.001	21.468	3.799	0.176
268	0.000	19.334	4.072	0.231
270	0.000	19.249	3.310	0.263
269	0.000	18.694	3.923	0.187

TABLE II
CORRELATION MATRIX AND EIGENVALUES

cor1	cor2	cor3	cor4	cor5	evalue
1.00000	0.46358	-0.13590	0.17702	0.26165	1.89976
0.46358	1.00000	-0.09139	-0.29930	0.35570	1.26409
-0.13590	-0.09139	1.00000	-0.05422	-0.16907	0.94879
0.17702	-0.29930	-0.05422	1.00000	-0.42302	0.57655
0.26165	0.35570	-0.16907	-0.42302	1.00000	0.31082

TABLE III

EIGENVECTOR MATRIX WITH 2 FACTOR LOADINGS

evect1	**evect2**	**evect3**	**evect4**	**evect5**	**sqre -e**
-0.421649	0.587690	-0.323468	0.200618	-0.576153	1.37832
-0.579594	0.083017	-0.293059	-0.594919	0.466225	1.12432
0.206066	-0.343421	-0.879290	0.245661	0.078093	0.97406
0.360743	0.698451	-0.073790	0.228650	0.569477	0.75931
-0.560075	-0.204832	0.175752	0.702277	0.346812	0.55751

TABLE IV

MATRIX OF LOADING FACTORS BEFORE AND AFTER ROTATION

load1	**load2**	**load3**	**load4**	**load5**	**rload1**	**rload2**
-0.581166	0.660750	-0.315077	0.152331	-0.321213	0.071471	-0.877061
-0.798864	0.093337	-0.285456	-0.451727	0.259927	0.584973	-0.551998
0.284024	-0.386114	-0.856479	0.186532	0.043538	0.002816	0.479318
0.497218	0.785280	-0.071876	0.173616	0.317491	-0.867814	-0.332851
-0.771960	-0.230296	0.171192	0.533245	0.193352	0.756691	-0.276363

TABLE V

NORMALIZED VARIMAX ADJUSTED CLUTTER VALUES

z1	**z2**	**z3**	**z4**	**z5**
-1.16666	-0.50987	0.39452	0.40764	-0.32430
-1.30402	-0.50987	0.48880	1.96582	-0.46864
-1.38250	0.43143	1.78916	-2.04733	0.47512
-1.41193	-0.98051	-1.19378	-0.08840	0.29747
-1.45118	0.90207	0.59282	-1.95205	1.05248
-0.28369	-0.03922	-1.11854	-0.56482	1.56323
-0.18559	0.43143	-0.50180	-0.54800	-0.84615
0.14798	0.90207	-1.36886	-0.53119	-0.54637
0.26571	1.37272	-1.01451	0.15542	0.16423
0.26571	0.90207	-1.10600	-0.18928	-0.84615
0.25590	0.43143	-1.26298	-0.73857	1.60764
0.30495	-0.98051	-1.23279	-0.26215	-0.69071
0.25590	-0.98051	-0.57843	1.38571	-0.63519
1.70789	2.78466	0.72100	0.20306	-0.17996
1.78638	0.43143	-0.21201	0.63184	0.07541
2.56143	1.37272	-0.07779	-0.06037	3.02884
0.29514	-0.50987	1.72182	-1.39155	0.30857
0.12836	-0.98051	-0.30164	0.42446	0.09762
0.16760	-0.50987	0.02252	0.57019	0.03100
0.39325	-0.50987	1.38744	1.23438	-1.23476
-0.23464	-0.50987	1.54023	0.41325	-1.15704
-0.38180	-0.98051	0.54917	1.17833	-0.54637
-0.36218	-0.98051	0.50969	-0.95716	-0.19107
-0.37199	-0.98051	0.25194	0.76076	-1.03490

TABLE VI
RELATIVE CLUTTER

ZT1	ZT2	REL_CLUT
-0.42463	0.88434	0.60806
-1.37753	0.47970	-1.58943
1.72671	1.95051	5.79679
-0.08705	0.75668	0.98251
1.99011	1.35752	5.35337
0.94522	-0.14882	1.35949
0.05803	0.07916	0.21512
0.24005	-0.59225	-0.48137
0.30234	-0.99414	-0.97635
-0.08033	-0.66320	-1.12316
1.15835	-0.61286	1.02421
-0.53288	-0.13498	-1.09276
-1.42189	-0.45552	-3.05795
0.55108	-1.70340	-1.61764
-0.34047	-1.50341	-2.81104
1.57812	-2.26580	-0.73788
0.88103	1.00216	2.96807
-0.51905	-0.02833	-0.91060
-0.47705	-0.13306	-0.99648
-1.34290	0.08252	-2.12365
-0.78055	0.78481	-0.13580
-1.14966	0.36760	-1.37533
0.24164	1.03845	1.95249
-1.13869	0.45230	-1.23070

As mentioned earlier, the focus of this paper is the different ways to determine how many loading factors to use in the computation of relative complexity. Following are the different ways in which the number of factor loadings can be chosen:

1. The number of loading factors can be based on the number of eigenvalues that are greater than unity from the correlation matrix. In this case we find from Table II that there are two eigenvalues that are greater than unity hence two factor loadings are to be used. From Table II these values are 1.89 and 1.26.

2. The number of loading factors can be also be based on the number of ratios of the eigenvalues that are less than 10. Arrange the eigenvalues of the correlation matrix in ascending order, of λ_1, λ_1 , λ_3 ,... λ_n , and determine the ratios as follows;

$$\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, \ldots \frac{\lambda_1}{\lambda_n}.$$

In the example under consideration,

$$\frac{\lambda_1}{\lambda_2} = \frac{1.89}{1.26} = 1.5,\ \frac{\lambda_1}{\lambda_3} = 2.01.$$

The other ratios are less than 10 also., so all eigenvalue ratios are selected and therefore five factor loadings are to be used by this method.

3. Determine the number of factor loadings by considering the ratios; $\frac{\lambda_1}{\sum \lambda_i}, \frac{\lambda_2}{\sum \lambda_i}, \ldots$. For the example under consideration these ratios are, $\frac{1.89}{5} = 0.38, \frac{1.26}{5} = 0.25$. The sum is given by $\sum$=5. If the ratio is greater than 0.1, the “normal factor”, then we select that ratio. For the case under consideration we now get four factor loadings.

4. Determine the average of eigenvalues and use this number in the denominator of method (3), such as

$$\frac{\lambda_1}{\frac{\lambda_1 + \lambda_2 + \ldots \lambda_n}{n}}$$

Which for this case gives a value of unity in the denominator so all are greater than 0.1, so five factor loadings are to be chosen.

5.Method (3) with a geometric average of eigenvalues in the denominator, such as,

$$\frac{\lambda_1}{\left(\frac{\lambda_1^2 + \lambda_2^2 + \ldots \lambda_n^2}{n}\right)^{1/2}}$$

which for the present case gives 1.6 and 1.1 as the two ratios greater than one, hence two factor loadings are chosen.

6. Use the quadratic average in the denominator of method (3),

$$\frac{\lambda_1}{\sqrt[n]{(\lambda_1 * \lambda_2 * \ldots * \lambda_n)}}.$$

For the present case this ratio gives 5 ratios greater than one hence 5 factor loadings should be used.

The result of the six methods for selecting the number of factors above give 2 occurrences of 2 factors and 2 for 5 factors, and 1 occurrence of four factors. Since using 4 and 5 factors is very unusual, they shall be discarded and the 2 factor solution chosen.

III. Algorithm for the Probability of Detection

In recent papers, Rotman et al. [14], Gerhart et al. [15] and Meitzler [16] review the classical NVL model and others, for computing the probability of detection, P_d and suggests a way to include clutter in the algorithm for P_d . However, no mention is made of how to compute the properly scaled clutter factors alluded to in the text of the papers. We suggest a method for obtaining clutter factors based on other validated clutter measures that can be used in this equation. The probability of acquisition of a target as a function of time is given by,

$$P(t) = P_\infty \left[1 - \exp\left(\frac{-P_\infty t}{3.4}\right)\right] \qquad (4)$$

or,

$$P(t) = \frac{\rho}{CF}\left[1 - \exp\left(\frac{-(\rho / CF)t}{3.4}\right)\right]. \qquad (5)$$

In (5),

ρ = an estimate of target acquisition probability over an infinite amount of time when the target is in the field of view.[15].

$$\rho = \frac{(n / n_{50})^E}{1 + (n / n_{50})^E} \qquad (6)$$

where,

n= the number of resolvable cycles across the target

n_{50}= the number of cycles required for P_∞ to equal 0.5

$E = 2.7 + 0.7\,(n/n_{50})$

CF = a clutter factor.

In [14] it is shown that,

$$\left(\frac{n}{n_{50}}\right) = \frac{\ln\left(\frac{\Delta T\sqrt{\varepsilon / 7}}{MRT_0}\right) - R\beta_{atm}}{\frac{\gamma}{s}\beta_{sys} R}. \qquad (7)$$

Hence (5) can be written as a function of ΔT and the clutter factor, relative or otherwise. Or, the probability of detection P(t), can now be computed as a function of ΔT, range from target to sensor, atmospheric condition, and sensor system parameters. In the following section we give results for the NVL terrain board images and our relative clutter measure.

IV. Probability of Detection Results with Relative Clutter

Equations (4) through (7) were computed using a relative clutter measure for the clutter factor in a spreadsheet. The results are shown in graphical form below in Fig.'s 1 and 2.

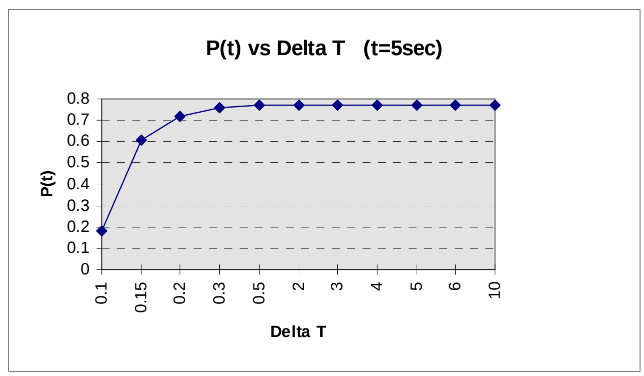

Fig. 1 Pd versus Delta T

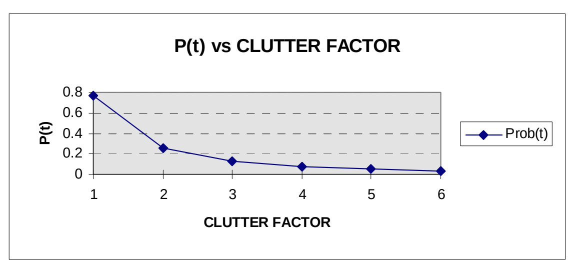

Fig. 2 Pd versus clutter

As discussed in [15], the effect of ΔT quickly approaches an asymptotic value. The results in Fig. 2 show how quickly clutter effects the Pd. Below in Fig. 3 is one of the images used in this study,

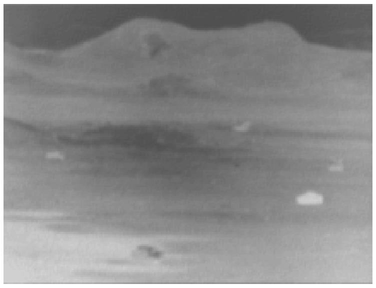

Fig. 3 Night Vision Laboratory Terrain board image courtesy of Dr. Barbara O'Kane

V. Conclusions

In this paper a new metric, the relative clutter metric, has been proposed for aggregating many diverse clutter metrics. The new relative clutter metric has been used in the computation of the probability of detection. Different methods for objectively selecting the number of factor loadings has been suggested. Future papers will show how to assess the perceptual worth of the various clutter metrics based on statistical signal detection theory, experimental psychophysical tests, and validated visual perception algorithms[7,8].

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Author Biographies

Thomas J. Meitzler, received his B.S. and M.S. in Physics from Eastern Michigan University and a Ph.D. in Electrical Engineering from Wayne State University in Detroit, Michigan. His Ph.D. thesis was titled "Modern Approaches to the Computation of the Probability of Target Detection in Cluttered Environments." He has held teaching positions at The University of Michigan-Dearborn and Henry Ford Community College.

From 1988 to present he has been a research scientist at the U.S. Army TACOM Research and Engineering Center (TARDEC), Survivability Technology Center. His present areas of interest are the validation, verification, and development of electro-optical and visual acquisition models, and experimental visual perception studies in the TARDEC Visual Perception Laboratory. He is a cowinner of the 1995 US Army Research and Development Achievement Award and has co-authored several papers in the fields of target detection and infrared and visual system simulations.

Grant Gerhart, finished his B.S. and Ph. D. degrees in Physics at Iowa State and Wayne State Universities in 1966 and 1972 respectively. From 1972 until the present he has been a research physicist at the U.S. Army Tank-automotive RDE Center (TARDEC) where he presently holds the position of Senior Technical (ST). He is an adjunct professor at both the Wayne State and Oakland University Engineering Departments. He is the author of more than 100 peer review articles and conference proceedings and holds four patents. He also participates on numerous international committees including both NATO and bi-lateral expert groups in ground vehicle survivability. Dr. Gerhart is currently involved in the analysis of polarized light for signature analysis applications and early vision models for target detection and discrimination.

Euijung Sohn, studied at the University of Illinois and got her B.S. degree in Electrical Engineering.
After her graduation, Mrs. Sohn was hired in Simulation department in U.S. Army Tank Automotive Command in 1991. She was involved in the various type of terrain simulation with the six degree of freedom moving simulator and analyzed the results from many test sensors. Mrs. Sohn has worked as a research engineer from 1992 to present 1995 in the Survivability Center. She has been involved in the validation, and verification of thermal and visual detection models and atmospheric propagation studies. Mrs. Sohn has co-authored several technical papers in the area of infrared and visual system simulations and target detection.

Harpreet Singh, received his B.Sc. in Engineering. from Punjabi University in 1963. He received a Ph.D. in Electrical Engineering from the University of Roorkee, India in 1971. He was with the Electronics and Engineering dept. of Roorkee from 1963 to 1981. He developed a postgraduate program in computer engineering at the Univ. of Roorkee. He was the winner of the Khosla Award (highest) in 1971 from the Univ. of Roorke. He joined WSU in 1981 and is presently serving as a professor in this Univ. He has over 200 publications in international journal and publications. He has also served as the Associate chair of the dept. of Electrical and Computer Engineering for several years. His current areas of interest are, computer vision and target detection, system theory, fuzzy and neural networks, and software engineering.